Blockchain Research Lab

BRL Working Paper Series No. 16

How Elon Musk's Twitter activity moves cryptocurrency markets

Lennart Ante [1, *]

[1] Blockchain Research Lab, Max-Brauer-Allee 46, 22765 Hamburg, Germany

* Correspondence: ante@blockchainresearchlab.org

Revised version: 12 Jan 2022

(Original version: 03 Feb 2021)

Abstract: Elon Musk, one of the richest individuals in the world, is considered a technological visionary and has a social network of over 69 million followers on social media platform Twitter. He regularly uses his social media presence to communicate on various topics, one of which is cryptocurrency, such as Bitcoin or Dogecoin. Using an event study approach, we analyze to what extent Musk's Twitter activity affects short-term cryptocurrency returns and volume. In other words, we investigate whether cryptocurrency markets exhibit a "Musk Effect". Based on a sample of 47 cryptocurrency-related Twitter events, we identify significant positive abnormal returns and trading volume following such events. However, we discover that on average, price effects are only significant for Dogecoin-related Tweets but not for Bitcoin. This is because regarding the latter, the significant price effects of positive and negative news cancel each other out, as further classification and analysis of Bitcoin-related tweets reveals. Our study shows the significant impact that the social media activity of influential individuals can have on cryptocurrencies. This suggests a conflict between the ideals of freedom of speech, morals and investor protection.

Keywords: Twitter; Bitcoin; Dogecoin; Event study; Social media

1 Introduction

On January 29, 2021, *Elon Musk*, at that time the richest person in the world (Klebnikov, 2021), unexpectedly changed the bio[1] of his Twitter account to *#bitcoin*. The price of *Bitcoin* rose from about $32,000 to over $38,000 in a matter of hours, increasing the asset's market capitalization by $111 billion. The relevance of Musk's tweets for financial markets has already become apparent in other contexts. His tweet "considering taking Tesla private at $420" (Musk, 2018) resulted in a fraud charge and a penalty of $40 million (U.S. Securities and Exchange

[1] The Twitter bio is a prominent area on a Twitter account page where users can describe themselves in 160 characters.

Exhibit W
Johnson V. Musk et al
Case No.: 1:22-cv-05037

Commission, 2018). Musk's endorsement of the encrypted messaging service *Signal* (Musk, 2021a) led to investors purchasing the unrelated *Signal Advance* stock, increasing the latter's market valuation from $55 million to over $3 billion (DeCambre, 2021). These events clearly show the impact that leadership in social networks can have on financial markets and the decision-making behavior of (individual) investors.

While the market may interpret Musk's tweets about Tesla as "accurate news", his tweets about cryptocurrency at least to some degree represent moods or personal sentiment—which have been shown to predict financial market pricing (Bollen et al., 2011; Gabrovšek et al., 2017; Schumaker and Chen, 2009). In a talk on social media platform *Clubhouse*, Musk stated that Bitcoin is "on the verge of getting broad acceptance" and disclosed that he is "late to the party but […] a supporter of Bitcoin". In the talk, he also claimed that his tweets about the cryptocurrency *Dogecoin* are only jokes (Krishnan et al., 2021). This is in line with his May 2020 tweet in which Musk said he "only own[ed] 0.25 Bitcoins" (Musk, 2020). However, it has become public knowledge that Tesla invested $1.5 billion in Bitcoin between January and March 2021 (U.S. Securities and Exchange Commission, 2021), suggesting that those Bitcoin-related tweets may have been more than "only jokes". Regardless of whether they are meant in jest or in earnest, Musk's tweets seem to affect the cryptocurrency market, which is our motivation to investigate the phenomenon in more detail and to discuss its implications. While Musk is by no means the only public figure to speak out about cryptocurrency or financial markets on social media, he is arguable among the most influential ones.

Social media play a significant role in strategic interactions of influential individuals such as managers, journalists or financial analysts with stakeholder groups (Heavey et al., 2020; Pfarrer et al., 2010). These individuals can use their social networks to shape their own reputation and identity or that of a related company (Deephouse, 2000; Zavyalova et al., 2012) by communicating directly with customers (Alghawi et al., 2014), controlling the timing of disclosure (Jung et al., 2017), or building trust with investors or communities (Elliott et al., 2018; Grant et al., 2018). However, the social media behavior of strategic leaders can also create much ambiguity. For example, it may be unclear whether a message reflects a mere mood or specific company-related information. Additionally, stakeholders may be flooded with extraneous information that distracts them from the core issues (Huang and Yeo, 2018). Critical behavior can accordingly damage the reputation of an individual or an affiliated company. Due to the fast-paced nature of social media, any such damage can occur instantaneously (Wang et al., 2019).

Various studies have analyzed the connection between cryptocurrency markets and social media activity—specifically Twitter. An increase in the number of Bitcoin-related tweets raises short-term Bitcoin liquidity (Choi, 2020), the number of Bitcoin-related tweets can explain Bitcoin trading volume and returns (Philippas et al., 2019; Shen et al., 2019), and Twitter sentiment can predict cryptocurrency returns (Kraaijeveld and De Smedt, 2020; Naeem et al., 2020; Steinert and Herff, 2018). Mai et al. (2018) show that social media users with lower previous cryptocurrency-related activity drive effects on cryptocurrencies, which makes sense: their actions are unusual or unexpected. If Elon Musk were to tweet about cryptocurrency several times a day, the market would likely come to regard this as noise. While several studies

have investigated the impact of individual tweets on stock market returns (Brans and Scholtens, 2020; Ge et al., 2019—both relating to stock market-related tweets of Donald Trump), to our knowledge, no studies—apart from those that cite the working paper version of the present article—have analyzed the impact of individual tweets on the returns and trading volume of cryptocurrency.

This article aims to identify how the social media activity of one of the world's most influential individuals affects cryptocurrency markets. To this end, we apply event study methodology, a common method to empirically test weak market efficiency in terms of pricing or trading volume. We extract cryptocurrency-related tweets by Elon Musk and classify them as unforeseen events. By comparing historical cryptocurrency market data to data around these events, it is possible to quantify the size of any effect that Musk's tweets had on the market.

The study addresses the question of how leadership, interaction and information in social media, specifically Twitter, affect investor attention and behavior in cryptocurrency markets. Elon Musk is of course but an extreme example, which is why our approach could almost be considered a case study. Ideally, the findings and implications can be transferred to other individuals and markets so that we may better understand the likelihood of social media personalities influencing cryptocurrency markets and whether, if so, this poses a problem.

The article is structured as follows: Section 2 describes the conceptual background and research questions. Section 3 lays out the data collection and estimation approach. Section 4 consists of descriptive results (4.1), general event study results (4.2), and more detailed event study results on Bitcoin-related events (4.3). In Section 5, we reflect on the results and provide an overview of limitations and future research avenues. Section 5 concludes.

2 Conceptual background and research questions

2.1 Information and consumer decision-making

Information in its many forms is an essential decision-making basis for consumers (Admati and Pfleiderer, 1988). Advances in information technology have made it much easier, cheaper and faster to produce, send, collect and process information (Johnson, 2001). As a result, the role of information in decision-making has shifted. While the key used to be to simply have enough information, today information abounds, so filtering it in a meaningful way has become the real challenge (Lee and Cho, 2005). Consumers in particular face information overload. Even if they are not overwhelmed by the inflow of information, they face the difficulty of allocating their limited time and attention across the multitude of information sources (Lee and Cho, 2005). The overabundance of information makes it difficult for individuals to properly process it, resulting for example in psychological problems, shorter attention spans or poor decision marking (Agnew and Szykman, 2005; Hu and Krishen, 2019; Jacoby, 1984). Information literacy, or financial literacy in the context of financial decision-making, is considered central to improving the decision-making of consumers and even firms (Lusardi and Mitchelli, 2007; van Rooij et al., 2011).

One solution for processing excessive information is to use external information intermediaries (Rose, 1999) such as online search engines, financial advisors, social media influencers or other

parties whose statements and opinions facilitate the consumers' information management (Lee and Cho, 2005). Personal sources can also help in this respect (Barrett and Maglio, 1999) and tend to be preferred over non-human sources in case of high uncertainty or importance (Coleman et al., 1996). Information overload is also a key characteristic of social media platforms (Feng et al., 2015; Sasaki et al., 2016) like Twitter. Such networks allow their users to follow the activity and opinions of other people or entities, identify experts, or engage in commercial transactions (Kleinberg, 2008). Users can often view the networks of other participants. On Twitter for example, someone with many followers can be regarded as an opinion leader. Features such as retweeting allow information to spread exponentially across the network, making social networks a powerful marketing and communication tool (Boyd and Ellison, 2007).

Influencers are individuals who enjoy great admiration, credibility and/or expertise with consumers. Scheer and Stern's (1992) *influence framework* describes the dynamics of the influencers' effect on consumer behavior. It states that an influential person can use his power resources, which include *information*, *expertise*, *prestige*, *service* and *attractiveness* (Dwyer et al., 1987; Gaski and Nevin, 1985), to exert influence over his network. For Elon Musk, the most relevant power resources are likely to be expertise (being a technology visionary) and prestige (being successful and rich). While Musk fully controls his messages on Twitter, the relevance and effect of his statements depend on the interpretation of his followers. A statement's power appeal is successful when the addressees respond with *satisfaction* and *trust*. The consumers then decide whether to comply with the influencer's statement or suggestion (Scheer and Stern 1992). The desire to comply is greater if there are good reasons for the consumer to behave accordingly (Ruvio et al., 2013). For example, a statement that Dogecoin may be "The future currency of Earth" (Musk, 2021b) could motivate especially those people to buy Dogecoin who fundamentally believe in cryptocurrency or who regard Musk as a role model and expect similar (financial) success from following his views and lifestyle.

The social psychology phenomenon of *transference* means that effects of past relationships are transferred to future relationships. People use existing information and emotions to evaluate new information (Andersen and Baum, 1994). Studies on advertising and marketing have shown that characteristics and attitudes associated with influential people, such as trustworthiness or expertise, are transferred to the advertised products (Debevec and Iyer, 1986; Langmeyer and Walker, 1991; Ohanian, 1991). If Elon Musk is perceived as a successful entrepreneur who communicates via Twitter about technological innovations in the automotive industry or space travel, Twitter users may take the cryptocurrencies he tweets about to be equally *innovative* or *successful* (in terms of financial returns). This could be explained by cognitive balance theory (Heider, 2013). Musk's followers want to achieve a balance of their attitudes towards Musk and his statements or beliefs. If Musk "promotes" cryptocurrencies like Bitcoin or Dogecoin, the followers' trust in Elon Musk spills over to the cryptocurrencies.

2.2 Information and financial markets

The *efficient market hypothesis (EMH)* posits that "prices fully reflect all available information" (Fama, 1970). The price of an asset reflects a supply and a demand curve, whose intersection marks an equilibrium that satisfies consumers (e.g. Bitcoin investors) and

Exhibit W
Johnson V. Musk et al
Case No.: 1:22-cv-05037

producers (e.g. Bitcoin miners). The curves shift as new relevant information emerges. A tweet from Elon Musk may constitute such new information, which—if deemed relevant—is priced accordingly. However, much doubt has been cast on the validity of the EMH, as it is mainly based on the preferences and behavior of market participants. The *adaptive markets hypothesis (AMH)*, an extension of the EMH, holds that the degree to which information is reflected in prices depends on environmental conditions and the number and characteristics of the market participants (Lo, 2004), which makes market efficiency context-dependent. If few market participants have the same demand for scarce goods, this market will be much more efficient than a market with fewer market participants who demand more easily available goods. Applied to the cryptocurrency market, this would mean that the relevance of Musk's tweets (besides the actual informative quality of the tweet) also depends on external conditions such as historical volatility, environmental attention or regulatory uncertainty.

The mass of data that are available on the internet and especially via social media poses a challenge for financial models, systems and theories. Market participants must learn to correctly identify, process and interpret information. Research on financial markets, such as stocks (e.g., Bollen et al., 2011) and cryptocurrencies (e.g., Steinert and Herff, 2018), has already addressed this topic. While most research focuses on overall sentiment or mood, some articles have also identified the relevance of influential individuals and their social media communication on stocks (Brans and Scholtens, 2020; Ge et al., 2019) and cryptocurrencies (Cary, 2021; Huynh, 2021).

A fundamental aspect of the impact of individuals on financial markets is the quality of the information provided. *Signaling theory* holds that an agent can use quality signals to reduce information uncertainty in a market (Spence, 1973). While such signals are mostly used in an agent’s own interest, for example individuals applying for a job (Spence, 1973) or entrepreneurial financing (Ante et al., 2018), it seems possible that, even without an ulterior motive or even unintentionally, a tweet from a very influential or reputable person is interpreted by a considerable number of market participants as a signal of the quality of the object of the tweet. Every tweet springs from some motivation, and be it only a fleeting mood. In this context, trust in the signal and its quality is of essential importance. To be trustworthy or credible, a signal must usually be associated with direct or indirect costs (Connelly et al., 2011). In the case of Elon Musk's tweets, the costs are of an indirect nature, and they consist in the potential damage to his reputation as a technological visionary and successful entrepreneur (i.e. his influencer status) or the reputation of the firms he is associated with (Wang et al., 2019). In addition, there is a risk of counter-signaling, i.e. of other agents sending opposing or critical signals (Feltovich et al., 2002). If, for example, the market were to learn that Musk’s tweets are not quality signals but noise, it should discard the information as irrelevant.

2.3 Research questions

Since Elon Musk and other influential individuals are likely to continue to publicly comment on cryptocurrency for the foreseeable future, we raise the following research questions to add to the literature on the informational efficiency of cryptocurrency markets and the attention their participants devote to influencers:

> *RQ1: What effect do Elon Musk's cryptocurrency-related tweets have on the pricing and trading volume of cryptocurrency?*

The answer to this question can indicate the extent to which tweets can generally be considered quality signals or whether the observed market effects were merely coincidental. Secondly, the AMH suggests that a less efficient or liquid cryptocurrency will experience a stronger impact of Musk's tweets. We will therefore differentiate the effects by the type of crypto assets (Dogecoin versus Bitcoin):

> *RQ2: Do the effects of Musk's cryptocurrency-related tweets differ by cryptocurrency?*

Answering these two research questions will allow us to quantify and better understand the effect that social media influencers can have on cryptocurrency markets and to draw some conclusions regarding the interpretation of future events. That way, market participants can better assess the relevance of Musk's tweets and possibly other (social media) influencers. In addition, the results may contribute to the wider research on the role of social media leaders in influencing investor behavior, on assessing influencer content quality in the context of signaling theory, and on understanding influencer relevance for the efficiency of financial markets.

3 Data and Methods

3.1 Data collection and processing

The basis of the analysis are the tweets that Elon Musk posted between April 2019 and July 2021 (*twitter.com/elonmusk*). The relevant cryptocurrency-related events were identified by multiple steps. First, we included only Musk's original tweets but not his answers to other Twitter users' activity because otherwise it would be unclear whose followers are being addressed and when Musk's followers might see the response. Furthermore, the Twitter users whom Musk responds to might themselves have some influence on cryptocurrency markets, which would compromise the event study methodology (MacKinlay, 1997).

We systematically searched all of Musk's tweets for terms such as *Bitcoin*, *BTC*, *Doge*, *Ether*, *ETH*, *Crypto*, and the names and tickers of other major cryptocurrencies (which, however, yielded no results). This search produced an initial sample of 42 tweets. In the next step, we manually screened Musk's tweets for cryptocurrency-related content, which yielded another 19 tweets. Finally, we validated our approach by studying media reports and articles on Musk's Twitter behavior in the context of cryptocurrency, as a result of which we identified six additional tweets. Accordingly, our sample includes 67 events of cryptocurrency-related tweets by Elon Musk. The tweets and their meta data are presented in the appendix.

For each tweet, we ascertain whether it refers specifically to Dogecoin (66%), Bitcoin (30%) and/or Ethereum (1.5%), or to cryptocurrencies in general (2.5%). We then identify and cluster successive tweets on the same topic (i.e. the cryptocurrency mentioned) in order to exclude any confounding effects in the event study. Whenever more than six hours elapsed between two subsequent tweets, this marks the beginning of a new cluster (event). This time interval ensures that the estimation periods for the quantitative analysis do not overlap (see below). With fourteen episodes of tightly-spaced tweets, we are left with a sample of 50 events. We exclude

tweets that mention cryptocurrency in general from the analysis, as they lack a comparable specific financial time series. Finally, for the period of the very first event (comprising two tweets), we were unable to obtain sufficiently high-resolution price and volume data for Dogecoin, so this event had to be excluded. Accordingly, the statistical analysis covers 47 events.

We retrieve minute-by-minute close prices, trading volume (in USDT) and the number of trades for DOGE/USDT, BTC/USDT and ETH/USDT from the API of the cryptocurrency exchange Binance for 361 minutes before until 120 minutes after each event. The reference asset USDT is *Tether dollar*, a blockchain-based stablecoin whose value is pegged to the US Dollar.

3.2 Event study methodology

Event study methodology is used to calculate the share of the identified returns and trading volume that is attributable to Elon Musk's Twitter activity. The expected return is calculated over an estimation period before an unexpected event and is compared to the observed return around the event. The difference between the expected and the observed return is the abnormal return that can be attributed to the event (Brown and Warner, 1985). We use the Constant Mean Return Model (Brown and Warner, 1985) to derive the expected returns and calculate log returns as $log(p_t/p_{t-1})$.. It calculates the expected return (ER_{it}) as the average log return over the estimation period: $ER_{it} = \overline{R_{it}} + e_{it}$, where i identifies a specific event and t denotes the minute within the estimation period. R_{it} is the absolute return of the cryptocurrency over minute t for transaction i, and e_{it} is the error term. The bar over R_{it} indicates the mean across the estimation window. The abnormal return (AR) can then be calculated by subtracting the observed from the expected return: $AR_{it} = R_{it} - ER_{it}$. Across multiple events of the same type, e.g. tweets, ARs can be aggregated into the average abnormal return $AAR_{it} = \frac{1}{N}\sum_{i=1}^{N} AR_{it}$ or as a cumulative abnormal return: $CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$, which can in turn be aggregated into cumulative average abnormal returns (CAARs) for multiple events.

We use a 5-hour period before the event (t = -360 to -60 minutes) as the estimation window—long enough to make the results robust (Armitage, 1995). Abnormal trading volumes are calculated in the same way as abnormal returns. To ensure comparability between Bitcoin and Dogecoin we measure trading volumes in USDT. As suggested in the literature on abnormal trading volumes in other financial markets (Ajinkya and Jain, 1989; Cready and Ramanan, 1991), we use logged volumes, specifically a *log(x+1)* transformation to account for periods with no trading (e.g., Campbell and Wasley, 1996; Chae, 2005).

To assess the significance of the abnormal returns and trading volumes, we calculate parametric t-tests and the non-parametric Wilcoxon sign rank test (Wilcoxon, 1945), since such financial data is non-normally distributed (Brown and Warner, 1985). Only if both tests indicate significance do we consider a result valid.

4 Results

4.1 Descriptive statistics

Figure 1 shows cumulative log returns from 360 minutes before to 120 minutes after a cryptocurrency-related tweet by Elon Musk. The group “all” includes returns of Bitcoin, Ether and Dogecoin, while the other two graphs only for Dogecoin or Bitcoin. Ethereum (N=1) is omitted. Across all 47 events, a price jump of about 3% occurs following the dissemination of the information. Prices continue to rise over the next hour or so before declining again. Prior to the events, the average returns fluctuate but begin to rise in the last hour before the tweet.

Distinguishing between events related to Dogecoin versus Bitcoin provides further insight into the composition of these effects. Tweets about Bitcoin tend to be posted during times of falling Bitcoin prices (about -2% in the six hours before a tweet), while tweets about Dogecoin occur when the cryptocurrency has gained about 2% in the last six hours. This may indicate that Musk's Dogecoin-related tweets are a reaction to increases in the cryptocurrency's value, while Bitcoin-related tweets are more likely to be a reaction to falling prices. An analysis of the mood or sentiment of the individual tweets may offer better conclusions in this respect (see Section 4.3 below).

While the prices of both Bitcoin and Dogecoin react positively to the events, the reactions differ significantly. Bitcoin exhibits a small, short price spike followed by a gradual increase for about 45 minutes. After that, the returns level off. Dogecoin shows an instant and very large price spike, followed by another 45 minutes of price increase. After that, the returns revert back to the level of the initial price spike. Overall, the events have a positive price effect which persists for at least two hours.

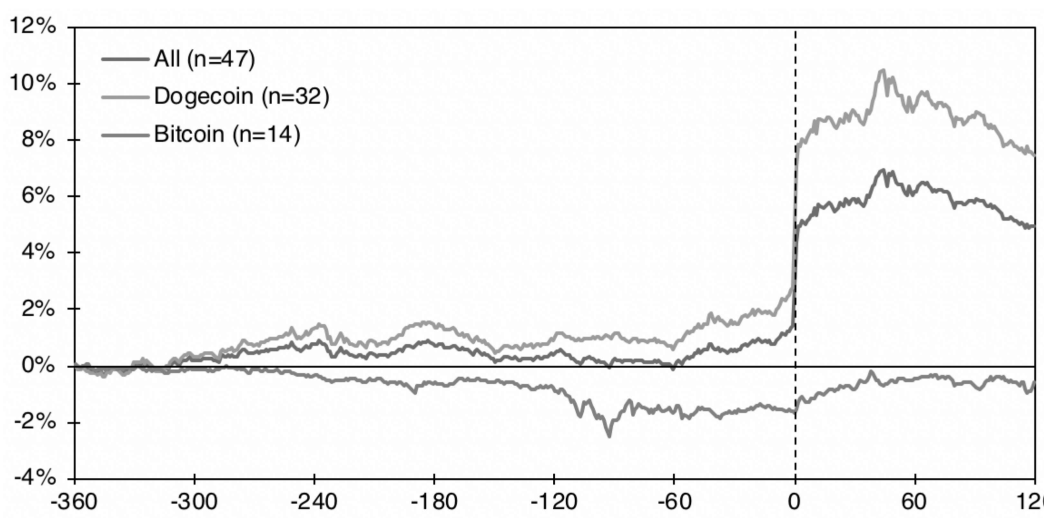

Figure 1. Cumulative log returns around a cryptocurrency-related tweet.

Figure 2 shows the log-transformed trading volume both jointly and separately for Dogecoin and Bitcoin around a cryptocurrency-related tweet by Elon Musk. The trading volumes are relatively stable before the posting of a tweet and increase sharply at the time of publication. As with the returns, the relative effect is significantly larger for Dogecoin than for Bitcoin.

Exhibit W
Johnson V. Musk et al
Case No.: 1:22-cv-05037

Over the two hours after the tweet and associated spike, the trading volume of Bitcoin declines somewhat. The drop is more pronounced for Dogecoin, yet the volume remains well above the pre-tweet level. For both returns and trading volume, the sudden increase in response to the tweet takes only about two to three minutes (see below).

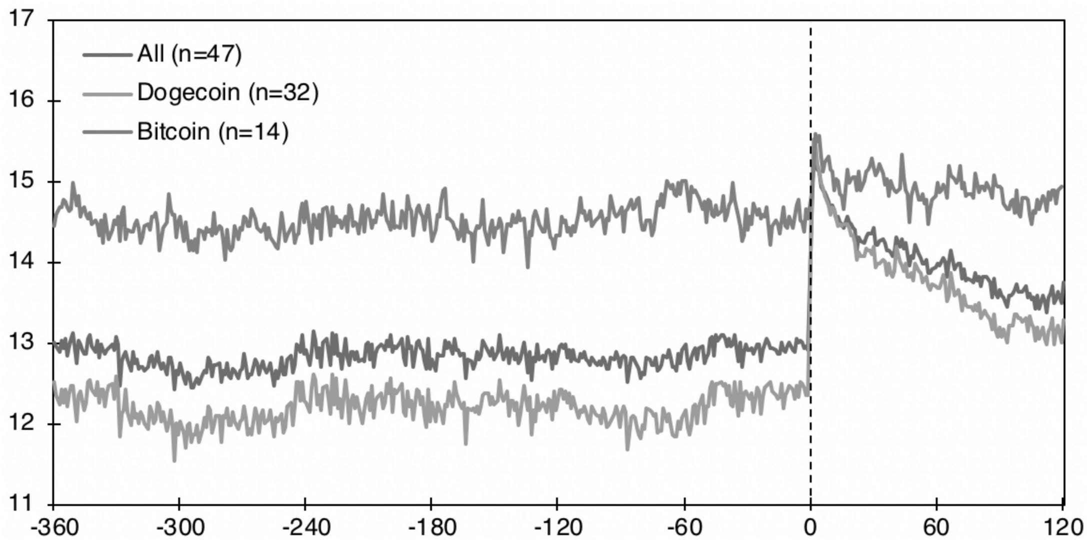

Figure 2. Log-transformed trading volume around a cryptocurrency-related tweet.

4.2 Event study results

Table 1 shows event study results for cryptocurrency log returns for the entire sample, Dogecoin-related events, and Bitcoin-related events. Abnormal returns are shown for the minute of the event, for each of the following ten minutes, and aggregated over seven different intervals. That way, we can determine both short-term effects and cumulative effects. In addition to the abnormal returns, we present a parametric (*t-test*) and a non-parametric (*z-test*) significance test, as well as the proportion of the events that exhibit positive abnormal returns (*pos*). Table 2 contains analogous information for cryptocurrency trading volumes.

Looking at the abnormal returns of all events, we find highly significant positive effects in the minute of the event and the next two minutes. The effect in the event minute is 1.46%, with 83% of the events exhibiting positive returns. In minute t+1, the effect is 1.50% (77% positive), and in t+2, the effect levels off at 0.62% (64% positive). Thereafter, the abnormal returns are generally much lower and no longer significant. Surprisingly, however, we find another positive significant abnormal effect in t+10. Overall, we can conclude that the market reacts quickly and significantly to Musk's tweets, but just as quickly reverts back into its normal state. This is also evident from the CARs, which are significantly positive for all periods considered, varying only slightly in absolute value (3.5 to 4.8% in all periods beyond two days). 91% of the events resulted in a positive abnormal return over the [0, 5] period. The other periods also feature significantly more positive than negative results, with a lowest value of 72% positive events in [0, 60].

Significant effects also abound with respect to the Dogecoin subsample. The very minute Musk posts a Dogecoin-related tweet, the market reacts with an abnormal return of 2.16%, followed

Exhibit W
Johnson V. Musk et al
Case No.: 1:22-cv-05037

by another 2.16% in the next minute. After minute three (0.79%), the effects are no longer significant. The CARs are positive and significant in all periods considered, with a maximum of 6.33% in [0, 60], or about 0.1% per minute. Over a period of two hours, the CARs decline again, although at 4.43% they are still significantly positive. 84 to 97% of the events result in positive abnormal returns.

By contrast, for the 14 Bitcoin events, no significant effects can be identified. While the proportion of positive results exceeds 50% in all but one instance and the aggregate results are consistently positive, none of them achieve statistical significance. This stark difference between Dogecoin and Bitcoin could be due to the fact that Musk's Dogecoin-related tweets are almost exclusively positive, while his Bitcoin-related tweets are of mixed tone (cf. the appendix), so any effects may cancel each other out. This suggests that Bitcoin tweets should be further subdivided to generate more accurate insights.

The results on abnormal trading volumes displayed in Table 2 feature significant positive effects throughout – across all individual minutes, all intervals, and all events, as well as Dogecoin and Bitcoin. In the first ten minutes after the event, on average 81 to 91% of the events lead to positive abnormal trading volumes. The cumulative average trading volume increases continuously with longer periods, which indicates that the trading volume remains consistently elevated over the two hours after an event. However, the rate of increase declines slightly over time, as can be seen, for example, by comparing the periods [0;60] (96.919) and [0;120] (153.404), where the abnormal volume of the second hour amounts to only about 58% of that of the first hour.

The results are even stronger for Dogecoin. Over 90% of the events (except minute 0, at 88%) lead to significant positive abnormal trading volume in all minutes and intervals. This highlights the significant instantaneous effect of Musk's tweets on Dogecoin's trading volume that lasts for at least two hours. For Bitcoin, the significant abnormal trading volume increases from minute 0 (0.389) to its peak in minute 2 (1.148) and slowly decreases again thereafter. The effects are less pronounced than for Dogecoin, which is to be expected since Bitcoin is the significantly larger and more liquid asset. On average, between 79 and 93% of the events in the aggregated results are associated with positive CATVs.

Figure 3 shows abnormal returns (ARs), cumulative abnormal returns (CARs), abnormal trading volume (ATV) and cumulative abnormal trading volume (CATV) around Elon Musk's cryptocurrency-related Twitter events. The figure visualizes and complements the previous tables, e.g. by offering more minute-level observations, and facilitates a faster and clearer interpretation of the results. The positive ARs for the full sample and Dogecoin over the first three minutes are evident. In the second row of panels, the CARs are clearly significantly positive for the full sample and for Dogecoin and positive but insignificant for Bitcoin. In terms of trading volume, we see that the minute-by-minute effects of the full sample and Dogecoin are consistently significantly positive in each minute but decline in magnitude over time. For Bitcoin, the effects are insignificant at times (around 10 to 15 minutes) but then increase again. In the case of CATV, the monotonous increase in all three samples implies that the effects are consistently significantly positive throughout the 30 minutes after an event

Table 1. Event study results for cryptocurrency log returns. Abnormal returns (AR) and cumulative abnormal returns (CAR) of both cryptocurrencies, as well as Dogecoin and Bitcoin separately, around cryptocurrency-specific tweets by Elon Musk. '*z*-test' refers to the non-parametric Wilcoxon sign rank test. 'pos' is the share of observations with positive abnormal returns.

	(1) All events (n=47)				(2) Dogecoin events (n=32)				(3) Bitcoin events (n=14)			
Minute	AR	*t*-test	*z*-test	pos	AR	*t*-test	*z*-test	pos	AR	*t*-test	*z*-test	pos
[0]	1.4564%	5.23***	5.00***	83%	2.1586%	6.27***	4.88***	94%	-0.0537%	-0.89	-0.28	57%
[1]	1.5036%	4.55***	4.37***	77%	2.1552%	4.94***	4.08***	88%	0.1267%	0.85	1.10	57%
[2]	0.6235%	3.45***	2.86***	64%	0.7919%	3.26***	2.64***	66%	0.2833%	1.27	1.35	64%
[3]	-0.0323%	-0.14	0.38	62%	-0.1101%	-0.34	0.08	63%	0.1373%	0.72	0.09	57%
[4]	0.2275%	1.19	1.01	55%	0.3105%	1.12	0.97	53%	0.0582%	0.51	0.79	64%
[5]	-0.1606%	-1.05	-0.56	49%	-0.1546%	-0.71	-0.30	47%	-0.1875%	-1.39	-0.91	50%
[6]	0.1223%	1.13	0.77	55%	0.1739%	1.13	1.10	56%	0.0094%	0.11	-0.66	50%
[7]	0.1074%	0.82	0.74	51%	0.1516%	0.79	0.84	50%	0.0171%	0.27	0.60	57%
[8]	0.1028%	0.90	0.98	57%	0.0819%	0.50	0.37	53%	0.1537%	1.59	1.41	64%
[9]	-0.0211%	-0.12	-0.85	47%	-0.0378%	-0.15	-1.10	41%	0.0064%	0.11	0.72	57%
[10]	0.2896%	2.57**	2.21**	64%	0.4106%	2.67**	2.49**	72%	-0.0011%	-0.02	-0.72	43%
Window	CAR	*t*-test	*z*-test	pos	CAR	*t*-test	*z*-test	pos	CAR	*t*-test	*z*-test	pos
[0, 1]	2.9600%	5.83***	4.98***	83%	4.3138%	7.07***	4.56***	94%	0.0730%	0.52	0.85	57%
[0, 2]	3.5835%	6.03***	5.23***	87%	5.1057%	7.13***	4.73***	94%	0.3562%	1.03	1.54	71%
[0, 5]	3.6182%	6.41***	5.24***	91%	5.1515%	7.96***	4.81***	97%	0.3643%	0.80	1.48	79%
[0, 10]	4.2101%	6.26***	5.34***	89%	5.9316%	7.45***	4.88***	97%	0.5499%	1.04	1.54	71%
[0, 30]	4.4952%	4.66***	4.94***	87%	6.1676%	4.83***	4.73***	94%	0.9468%	1.16	1.29	71%
[0, 60]	4.7851%	5.07***	4.62***	72%	6.3322%	5.31***	4.54***	84%	1.5039%	1.23	0.47	43%
[0, 120]	3.5424%	3.83***	3.89***	79%	4.4325%	4.15***	3.68***	84%	1.6587%	0.89	0.91	64%

** and *** indicate significance at the 5% and 1% level.

Exhibit W
Johnson V. Musk et al
Case No.: 1:22-cv-05037

Table 2. Event study results for cryptocurrency trading volume. Abnormal trading volumes (ATV) and cumulative abnormal trading volumes (CATV) of both cryptocurrencies, as well as Dogecoin and Bitcoin separately, around cryptocurrency-specific tweets by Elon Musk. '*z*-test' refers to the non-parametric Wilcoxon sign rank test. 'pos' is the share of observations with positive abnormal trading volume.

	(1) All events (n=47)				(2) Dogecoin events (n=32)				(3) Bitcoin events (n=14)			
Minute	ATV	*t*-test	*z*-test	pos	ATV	*t*-test	*z*-test	pos	ATV	*t*-test	*z*-test	pos
[0]	1.829	6.64***	4.94***	81%	2.542	7.73***	4.60***	88%	0.389	2.45**	2.10**	71%
[1]	2.501	8.38***	5.46***	89%	3.379	10.43***	4.84***	94%	0.726	3.27***	2.54**	86%
[2]	2.569	8.70***	5.51***	89%	3.330	10.30***	4.86***	94%	1.148	3.65***	2.86***	86%
[3]	2.377	8.68***	5.56***	87%	3.078	9.94***	4.86***	100%	1.035	3.84***	2.73***	79%
[4]	2.360	9.06***	5.73***	89%	2.983	9.59***	4.84***	94%	1.125	4.88***	3.11***	86%
[5]	2.175	8.03***	5.51***	89%	2.841	8.90***	4.79***	94%	0.859	3.56***	2.73***	86%
[6]	2.126	8.13***	5.63***	89%	2.772	8.85***	4.82***	94%	0.666	3.31***	2.54***	79%
[7]	2.101	8.09***	5.58***	91%	2.695	8.40***	4.77***	94%	0.783	3.76***	2.86***	86%
[8]	1.977	7.38***	5.43***	87%	2.557	7.70***	4.71***	94%	0.859	3.93***	2.79***	79%
[9]	1.891	7.40***	5.34***	85%	2.452	7.95***	4.75***	94%	0.700	2.40**	1.92*	64%
[10]	1.930	7.73***	5.58***	89%	2.536	8.85***	4.86***	97%	0.667	2.88**	2.35**	71%
Window	CATV	*t*-test	*z*-test	pos	CATV	*t*-test	*z*-test	pos	CATV	*t*-test	*z*-test	pos
[0, 1]	4.331	7.82***	5.43***	89%	5.921	9.48***	4.79***	94%	1.115	3.75***	2.79***	86%
[0, 2]	6.900	8.26***	5.55***	89%	9.251	9.87***	4.84***	94%	2.263	4.16***	2.92***	86%
[0, 5]	13.812	8.54***	5.61***	91%	18.153	9.83***	4.88***	94%	5.283	4.40***	3.05***	93%
[0, 10]	23.837	8.37***	5.58***	89%	31.164	9.29***	4.81***	94%	8.958	4.09***	2.86***	86%
[0, 30]	56.782	7.70***	5.59***	89%	74.270	8.19***	4.79***	94%	20.202	3.80***	2.86***	79%
[0, 60]	96.919	7.26***	5.58***	89%	126.388	7.46***	4.77***	94%	33.657	3.87***	2.73***	79%
[0, 120]	153.404	6.34***	5.43***	91%	197.858	6.17***	4.58***	94%	57.720	3.64***	2.79***	86%

*, **, *** indicate significance at the 10%, 5% and 1% level.

Exhibit W
Johnson V. Musk et al
Case No.: 1:22-cv-05037

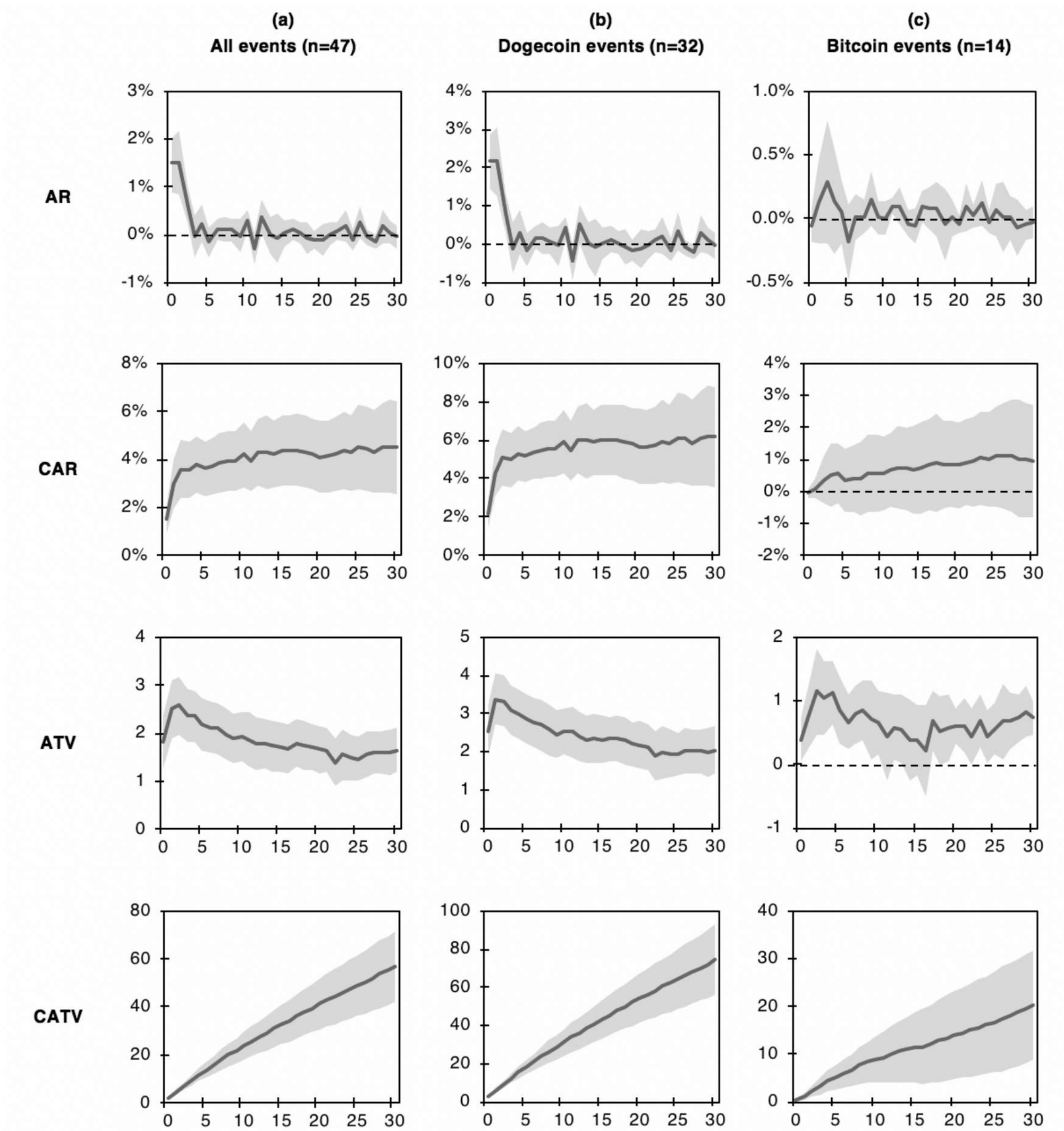

Figure 3. Cumulative abnormal returns and trading volume around cryptocurrency-related Twitter events of Elon Musk. Cumulative abnormal cryptocurrency log returns and trading volumes in the first 30 minutes following a cryptocurrency-related tweet by Elon Musk. The rows contain panels on *abnormal return (AR)* per minute, *cumulative abnormal return (CAR)* from 0 to 30 minutes, *abnormal trading volume (ATV)* per minute, and *cumulative abnormal trading volume (CATV)* from 0 to 30 minutes. Column (a) includes *DOGE/USDT*, *BTC/USDT* and *ETH/USDT* data, while the other columns refer to metrics on *DOGE/USDT* (b) and *BTC/USDT* (c). The grey areas mark 95%-confidence bands.

The results we have obtained so far already allow us to answer the research questions: Musk's tweets have a positive effect on the returns and trading volume of cryptocurrency over the intervals considered. The effects on returns differ significantly for Bitcoin versus Dogecoin. While Dogecoin-related events have significant positive effects on Dogecoin returns, an analogous effect does not exist for Bitcoin returns. As mentioned above, this may be because

Musk refers to Bitcoin both in a positive and a negative sense. This possibility will be examined in more detail in the next section.

4.3 In-depth analysis of Musk's tweets on Bitcoin

The 14 Bitcoin-related tweets (cf. the appendix) variously refer to neutral, positive or negative opinions or facts. Since some of them contain non-text elements, it is not possible to classify the tweets objectively using methods such as sentiment scoring or natural language processing. For a rough classification, we distinguish between a) non-negative (positive or neutral) and b) negative tweets. For this purpose, we asked three cryptocurrency experts to rate each tweet as either positive, negative, or unclear/neutral. It turned out that for each tweet, at least two of the experts agreed on the rating. On that basis, we classified 10 tweets as 'positive or neutral' and the remaining four as 'negative'. This subjective judgement and somewhat arbitrary classification naturally constrains the general validity of all derived results, which is why the data are presented so transparently that readers can devise alternative classifications.

Figure 4 shows cumulative log returns from 360 minutes before to 120 minutes after a Bitcoin-related tweet. The non-negative tweets clearly entail positive Bitcoin returns, while negative events appear to trigger a negative market reaction.

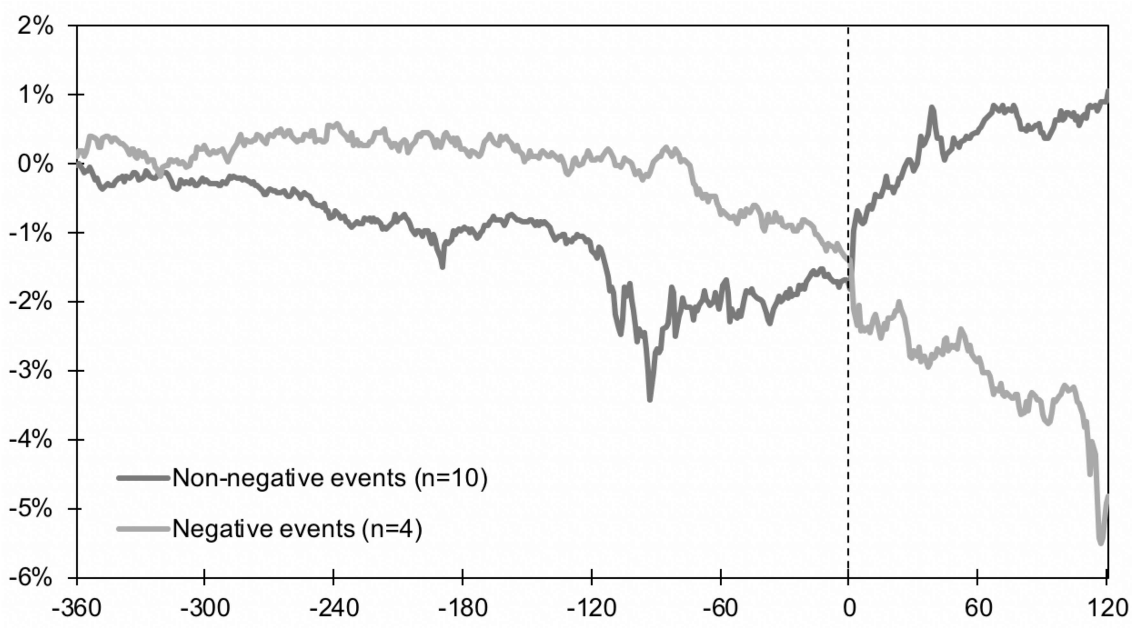

Figure 4. Cumulative log returns around non-negative vs negative Bitcoin-related tweets.